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From Anxiety to Action: How AI-FoMO Shapes Workers' Digital Commerce Entrepreneurial Intention

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Abstract

Generative AI is reshaping how workers form digital commerce entrepreneurial intentions, yet how AI-related fear of missing out (AI-FoMO) converts into proactive entrepreneurial behavior remains unclear. Drawing on social cognitive theory, this study tests a model in which AI-FoMO drives AI reliance, which in turn shapes two distinct cognitive routes: a tool-referenced route through perceived task automation (PTA) and an agent-referenced route through borrowed entrepreneurial competence (BEC), a newly proposed construct capturing how human–AI coupling reshapes workers' self-perceived capability for solo digital entrepreneurship. We further test whether digital self-efficacy (DSE) moderates the conversion of these perceptions into intention. Survey data from 328 Korean workers were analyzed using PLS-SEM. AI-FoMO predicted AI reliance (β = 0.391), which shaped both PTA (β = 0.531) and BEC (β = 0.291); both routes predicted entrepreneurial intention, and both serial mediation paths were significant, with the PTA route approximately 2.6 times stronger than the BEC route. DSE moderated only the BEC route (β = 0.105, p = 0.025), not the PTA route (β = −0.077, p = 0.109), an asymmetry confirmed by a formal coefficient-difference test. The findings reframe AI-FoMO as a potential driver of approach-oriented entrepreneurial behavior, introduce BEC as an extension of vicarious experience to the human–AI context, and show that digital self-efficacy selectively regulates how AI-induced perceptions convert into entrepreneurial intention.

Keywords: AI-FoMO; borrowed entrepreneurial competence; digital commerce entrepreneurial intention; generative AI; platform innovation; AI-enabled services; PLS-SEM

1. Introduction

Emerging technologies, particularly generative artificial intelligence (AI), are accelerating structural change across digital platforms and reshaping the landscape of digital commerce. As AI tools become embedded in platform-mediated work, e-commerce operations, and digital business models, individual workers and prospective digital entrepreneurs face a rapidly transforming opportunity structure. A distinctive form of anxiety has emerged within this shift: the apprehension that one may fall behind colleagues, peers, or competitors who adopt AI tools more quickly. Industry surveys document this concern, with 67% of executives citing the fear of missing out as a key driver of AI investment [1], and EY's 2024 Work Reimagined Survey of over 17,000 employees across 23 countries documenting the rapid acceleration of generative AI use alongside widespread employee anxiety about AI-driven obsolescence [2]. This phenomenon, recently conceptualized as AI-related fear of missing out (AI-FoMO) [3], captures workers' anxiety about forfeiting the productivity, career, and opportunity dividends that AI adoption is perceived to confer.

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Within the context of digital platform transformation, understanding how this anxiety translates into proactive, opportunity-seeking behavior, including the formation of *digital commerce entrepreneurial intention*, has direct implications for platform innovation, digital commerce ecosystems, and the supply of new digital ventures that drive the next wave of platform-based value creation.

We focus on digital commerce entrepreneurial intention as the outcome because it is the entrepreneurial form most directly enabled by the operational and cognitive affordances of generative AI: solo, low-capital, platform-mediated, and functionally modular ventures in which AI can absorb the marketing, development, and operational tasks that once required a founding team. It is therefore the setting in which the capability-conversion mechanism we propose is most consequential and observable. In positioning the study, we also distinguish our gap from adjacent literatures. Research on technology and AI anxiety, perceived obsolescence, and workplace FoMO has documented the antecedents and well-being correlates of AI-related apprehension but has rarely traced its downstream, approach-oriented behavioral consequences; research on entrepreneurial intention and entrepreneurial self-efficacy has specified capability beliefs as proximal antecedents but has not theorized how sustained coupling with AI reshapes those beliefs; and research on digital entrepreneurship and AI-enabled services has emphasized supply-side platform affordances while leaving the user-side cognitive transformation underspecified. The present study addresses the intersection these streams leave open, namely the cognitive–behavioral mechanism through which AI-related anxiety is converted into entrepreneurial intention.

How AI-FoMO shapes worker behavior, however, remains poorly understood. The dominant framing of fear of missing out, inherited from social media research, treats it as a maladaptive emotional state linked to compulsive use, sleep disturbance, and diminished well-being [4,5]. Yet a growing body of work suggests that FoMO can also produce *approach-oriented* behaviors (i.e., active engagement, opportunity-seeking, and goal pursuit) [5,6]. This Janus-faced quality is especially salient in the AI context: the same anxiety that might be expected to produce defensive withdrawal could plausibly mobilize workers toward proactive AI engagement, and ultimately toward career-relevant action such as digital entrepreneurship. Whether AI-FoMO functions primarily as a defensive emotional response or as a generative force for proactive behavior is therefore an open empirical question with substantial theoretical and practical implications.

While preliminary evidence suggests that FoMO can enhance entrepreneurial intention, the *mechanism* through which AI-related anxiety transforms into entrepreneurial intent has not been examined. Three interrelated research questions emerge: **(RQ1)** Through what behavioral and cognitive mechanisms does AI-FoMO translate into digital commerce entrepreneurial intention? **(RQ2)** Do tool-referenced perceptions (e.g., "AI can automate my work") and agent-referenced perceptions (e.g., "I can act capably through AI") function as analytically distinct cognitive routes from AI engagement to entrepreneurial intention? **(RQ3)** Under what boundary conditions does the conversion of AI-induced perceptions into committed entrepreneurial intention strengthen or weaken? Addressing these questions is essential to building a mechanistic understanding of how AI engagement reshapes worker self-concept and career trajectory.

This study addresses these gaps by developing and testing an integrated model in which AI-FoMO mobilizes workers into a stable behavioral pattern of *AI reliance*, which in turn produces two analytically distinct cognitive routes that shape digital commerce entrepreneurial intention: a *tool-referenced* route via perceived task automation and an *agent-referenced* route via what we propose as borrowed entrepreneurial competence (BEC), the perception that one personally possesses the capability to launch a digital venture, formed through accumulated co-performance with AI on tasks beyond one's solo capacity. We

further examine whether digital self-efficacy moderates the conversion of these perceptions into intention. Drawing on social cognitive theory [7,8], we extend the classical concept of vicarious experience to the human–AI context, arguing that intimate co-performance with AI generates a structurally analogous but qualitatively distinct mechanism through which AI's competence is psychologically borrowed into the worker's self-concept. We test the proposed model using survey data from 328 Korean workers analyzed with PLS-SEM in SmartPLS 4.0. Our findings make four contributions. First, we reframe AI-FoMO as a Janus-faced construct, capable of producing not only avoidance and distress, but also approach-oriented behavioral intentions, including digital entrepreneurship. Second, we propose and empirically support borrowed entrepreneurial competence as a new construct that captures how human–AI coupling reshapes worker self-perception, extending Bandura's [8] vicarious experience to the human–AI context. Third, we document an asymmetric moderation pattern in which digital self-efficacy amplifies only the agent-referenced route, not the tool-referenced route, a finding that refines the agentic premise of social cognitive theory by showing that self-efficacy regulates perception-to-intention conversion selectively, engaging with self-referential cognitions but bypassing tool-referential cognitions.

2. Theoretical Background and Hypothesis Development

2.1. Theoretical Foundation: Social Cognitive Theory and the Emergence of AI-FoMO

Table 1 positions the present study relative to the adjacent literatures reviewed in this section. This study draws on social cognitive theory (SCT) as its overarching theoretical framework. SCT [7,8] provides a parsimonious account of how individuals interpret environmental demands, develop capability beliefs, and translate those beliefs into action. At the core of SCT is the principle of *triadic reciprocal determinism*, in which behavior, personal cognition, and environmental factors mutually shape one another. Two SCT mechanisms are central to the present research. First, *enactive coping*, the principle that individuals respond to environmental demands by taking action that reduces the perceived gap between threat and current state, explains how anxiety about technological change can mobilize behavioral engagement rather than withdrawal. Second, *vicarious experience*, the principle that capability beliefs are formed not only through direct mastery but also through observing successful performance, explains how exposure to capable agents in one's environment shapes self-perception. We later extend this second mechanism to the human–AI context to develop our central theoretical contribution (Section 2.2).

Table 1. Positioning of the present study relative to adjacent literatures.

Literature Stream	What It Explains	Gap This Study Addresses
Technology/AI anxiety, perceived obsolescence	Antecedents and well-being correlates of AI-related apprehension	Downstream, approach-oriented (entrepreneurial) consequences left untraced
Workplace FoMO	Compensatory technology engagement and its costs and benefits	Conversion of anxiety into career-relevant entrepreneurial intention not modeled
Entrepreneurial intention/entrepreneurial self-efficacy	Capability beliefs as proximal antecedents of intention	How sustained coupling with AI reshapes those beliefs not theorized
Digital entrepreneurship/AI-enabled services/platform innovation	Supply-side platform affordances that enable venture creation	User-side cognitive transformation underspecified
The present study	AI-FoMO to AI reliance to PTA and BEC to DEI, moderated by digital self-efficacy	Specifies the cognitive-behavioral mechanism converting AI anxiety into entrepreneurial intention

A construct increasingly relevant to workplace technology engagement is the fear of missing out (FoMO). Originally developed in social media contexts [9], FoMO is defined as

a pervasive apprehension that others might be having rewarding experiences from which one is absent. The construct has been extensively studied as a maladaptive emotional state associated with compulsive social media use, sleep disturbance, and diminished well-being [4,5]. However, recent scholarship has begun to reconceptualize FoMO as a multifaceted motivational state that can produce both avoidance- and approach-oriented behaviors depending on context [5]. Workplace FoMO research, in particular, has shown that the fear of being left behind can mobilize compensatory technology engagement, with both costs (burnout) and benefits (work engagement, message-checking behavior) for employees [6].

The diffusion of generative AI in the workplace has created a distinctive context in which FoMO takes on new significance. Industry surveys consistently document that the majority of knowledge workers report anxiety about being outpaced by AI-savvy peers, with ABBYY [1] finding that 67% of manufacturing IT decision-makers cite the fear of being left behind as a key driver of AI investment. This pattern has prompted scholars to introduce the construct of *AI-related FoMO*, the apprehension that one may fall behind, lose competitive standing, or forfeit opportunities by failing to engage with AI tools at the same level as their peers [3]. Unlike social-media FoMO, which centers on missed social experiences, AI-FoMO concerns missed *competence dividends*, productivity gains, career advantages, and entrepreneurial opportunities that AI adoption is perceived to confer.

Two clarifications situate our use of this construct. First, AI-FoMO is not introduced here as a new construct; we adopt the validated measure developed by Deng et al. [3], and our contribution lies in tracing its downstream, approach-oriented pathway rather than in coining the construct. Second, what distinguishes AI-FoMO from general technology or AI anxiety is its social-comparative core: it is anxiety defined by apprehension about falling behind relative to peers, rather than a diffuse unease about technology itself. This relative-deprivation structure, reflected in items that reference others gaining advantages or benefiting from tools one is not using, is precisely what licenses the approach-avoidance (Janus-faced) reading, because the natural action that closes a peer-relative gap is engagement rather than withdrawal. We nonetheless note, and return to in Section 5.4, that the present design does not include a direct discriminant test against an AI anxiety scale.

Despite the growing recognition of AI-FoMO as a distinct construct, research on its behavioral consequences remains limited. Most existing work has focused either on the development of measurement scales [3] or on AI-FoMO's role in initial technology acceptance [10]. What remains poorly understood are the *downstream behavioral pathways* through which AI-FoMO shapes worker cognition and career-relevant action. Drawing on SCT's enactive coping principle, we argue that AI-FoMO motivates a behavioral pattern of AI engagement that, over time, transforms how workers perceive their own capabilities and opportunities. The next section develops this argument by specifying AI reliance as a pivotal mediator and identifying two distinct cognitive routes through which AI engagement reshapes entrepreneurial cognition.

2.2. AI Reliance and Two Cognitive Routes to Entrepreneurial Cognition

We position AI reliance—a stable behavioral pattern in which workers habitually turn to AI tools as a default mode of completing work tasks [11,12]— as a pivotal mediator linking AI-FoMO to entrepreneurial cognition. We define AI reliance specifically as a habitual, default-mode behavioral pattern, which distinguishes it from one-off or exploratory AI use and from purely attitudinal acceptance of AI: reliance is established when turning to AI becomes the routine first response to a work task rather than an occasional or deliberated choice, consistent with the information-systems literature on habit and continuance [11]. Drawing on SCT's enactive coping principle, we argue that workers experiencing AI-FoMO

develop AI reliance over time: the most accessible action that reduces the perceived gap between current state and AI-savvy peers is to engage with AI tools directly and persistently, until such engagement becomes habitual. Once established, AI reliance produces two analytically distinct cognitive consequences.

The first is a *tool-referenced perception*, namely, perceived task automation (PTA), the cognitive appraisal that AI is capable of automating substantial portions of one's current work [13]. PTA arises through what Bandura [8] termed *direct mastery experiences* with AI: each successful instance of AI handling a task, drafting a report, automating an analysis, generating code, provides concrete evidence that AI can substitute for human effort in particular task domains. Through accumulating evidence, workers form a generalized appraisal of AI as a task-automating technology. PTA is a tool-referenced perception in the sense that the cognitive object is AI's capability, not the worker's own capability.

The second cognitive consequence is more consequential and constitutes the central theoretical contribution of this study. We propose borrowed entrepreneurial competence (BEC) as a worker's perception that they personally possess the capability to launch and operate a digital venture, where this capability belief is formed not exclusively through unaided personal mastery but through accumulated experience of co-performing with AI tools on tasks beyond the worker's solo capacity. BEC is an *agent-referenced perception*: the cognitive object is the worker's own self, but the source of the capability belief is coupling with AI.

The theoretical foundation for BEC lies in extending Bandura's [8] concept of vicarious experience to the human–AI context. In Bandura's classical formulation, vicarious self-efficacy is formed through *distant observation* of similar others succeeding at a task. We argue that human–AI coupling produces a structurally analogous but qualitatively distinct mechanism. When a worker repeatedly co-performs with an AI system that successfully handles tasks beyond the worker's solo capacity such as sophisticated coding, professional design, multilingual content creation, complex analysis, the worker observes a successful "performer" with whom they are *intimately coupled* rather than distantly related, contributing direction and judgment as a co-author of each output. Through repeated coupling, the cognitive boundary between AI's competence and the worker's own competence becomes psychologically permeable, and AI-derived performance outcomes are integrated into the worker's self-concept as personal capability. BEC thus differs from entrepreneurial self-efficacy (which arises from unaided personal mastery), from classical vicarious efficacy (which involves distant observation of similar others), and from technology self-efficacy (which concerns tool use rather than entrepreneurial action through tools) (Table 2). The decisive distinction is not the referent of the belief, which in both BEC and entrepreneurial self-efficacy is the self, but the attributed source of the capability: in entrepreneurial self-efficacy, the capability is owned, attributed to one's enduring competence formed through personal mastery, whereas in BEC, the capability is borrowed, attributed to, and contingent upon the human–AI coupling, such that the belief is expected to attenuate if AI support is withdrawn. This conceptualization is consistent with recent empirical findings that AI usage at work reshapes employee self-efficacy and downstream behavioral choices through accumulated co-performance experience [14].

Table 2. Borrowed entrepreneurial competence (BEC) versus related capability constructs.

Construct	Cognitive Referent	Source of Capability Belief	Stability/Contingency
Borrowed entrepreneurial competence (BEC)	The self	Borrowed from intimate human–AI co-performance	Contingent on AI coupling; attenuates if AI withdrawn
Entrepreneurial self-efficacy (ESE)	The self	Personal mastery and one's enduring competence	Stable, internally owned
Classical vicarious efficacy	The self	Distant observation of similar others	Relatively stable
Technology/AI self-efficacy	The tool/one's tool use	Confidence in operating the technology	Tool-specific, not entrepreneurial

Note. Existing tables and figures are renumbered in this revision following the insertion of Table 2 and Table 3.

PTA and BEC shape digital commerce entrepreneurial intention through different mechanisms. PTA reduces the *perceived effort cost* of a venture by mentally pre-distributing operational work to AI [15], whereas BEC removes a more fundamental motivational barrier, doubt about one's own capacity to act [8,16]. These two routes are particularly consequential in digital platform contexts, where the operational complexity that AI can absorb (e.g., algorithmic recommendation, automated customer interaction, content generation, predictive analytics) and the capability that AI augments (e.g., e-commerce store setup, platform-based service delivery) directly determine the feasibility of solo, AI-supported digital commerce ventures [15]. Recent JTAER scholarship on AI-driven digital commerce platforms similarly emphasizes that the psychological mechanisms through which AI engagement shapes user behavior, including reactance, substitution, and capability formation, deserve dedicated theorization [17]. The two routes thus operate as analytically distinct mediators between AI reliance and digital commerce entrepreneurial intention.

These two routes also map onto two literatures that have so far remained largely separate. The tool-referenced PTA route connects to the *AI-enabled services* literature, which examines how generative AI, algorithmic recommendation engines, predictive analytics, and conversational agents reconfigure the cognitive cost structure of platform-mediated work and consumption. From this perspective, sustained exposure to AI-enabled platform services lowers the perceived effort required to operate a digital commerce venture. The agent-referenced BEC route, in contrast, connects to the *platform innovation* literature, which has long examined platforms as architectures that enable new venture supply through modular resources, network effects, and reduced entry barriers [15]. Our framework contributes a previously underspecified link between these two streams: AI-enabled platform services not only lower technical friction, but also psychologically transfer competence into the user, thereby expanding the population of individuals who perceive themselves as capable of becoming platform-based entrepreneurs. Through this lens, platform innovation is not merely a supply-side phenomenon engineered by platform operators, but a co-evolutionary process in which user-side cognition, shaped by sustained AI engagement, becomes a structural condition for the emergence of new digital commerce ventures.

2.3. Digital Self-Efficacy as a Boundary Condition

The translation of cognitive perceptions into behavioral intention is not automatic. SCT holds that *self-efficacy*, the belief in one's capacity to execute the behaviors required to produce given attainments [8], serves as a critical regulatory mechanism that determines whether motivational and cognitive resources are converted into action. Workers with strong self-efficacy beliefs are more likely to set challenging goals, persist in the face of obstacles, and translate perceived opportunities into committed intentions; those with weak self-efficacy may recognize opportunities yet fail to act on them.

In the digital domain, digital self-efficacy (DSE) captures workers' confidence in their ability to learn, navigate, troubleshoot, and produce value using digital technologies [18,19]. DSE is a domain-specific generalized capability belief: it is broader than confidence in any single tool but narrower than global self-efficacy. Recent research examines how AI-related self-efficacy and AI-related anxiety jointly condition worker adaptation to AI-driven workplaces [20], motivating closer attention to the moderating role of digital competence beliefs in models of AI-induced behavior. Within our model, DSE serves as a *boundary condition*, a regulatory factor that conditions the strength with which AI-induced perceptions (PTA, BEC) translate into entrepreneurial intention.

Theoretically, DSE should amplify both perceptual routes. Workers high in DSE possess the underlying confidence to act on perceived opportunities: when they perceive that AI can automate work (PTA), a high DSE enables them to envision themselves orchestrating that automation in service of a venture; when they perceive themselves as competent through AI (BEC), high DSE enables them to convert that perception into committed intention. We therefore theorize symmetric positive moderation across both routes.

2.4. Hypothesis Development

Building on the theoretical foundation developed above, we propose an integrated serial mediation model (Figure 1) in which AI-FoMO mobilizes workers into AI reliance, which in turn produces two distinct cognitive routes (PTA and BEC) that shape digital commerce entrepreneurial intention, with digital self-efficacy moderating the conversion of perceptions into intention.

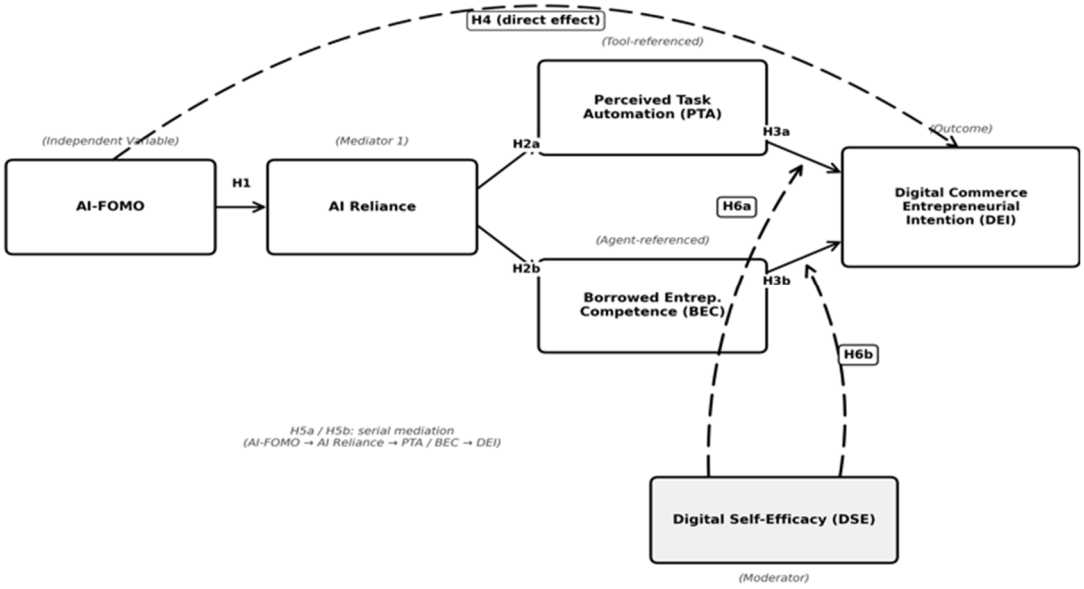


Figure 1. Conceptual research model. Note: AI-FoMO mobilizes workers into AI reliance, which in turn produces two analytically distinct cognitive routes shaping digital commerce entrepreneurial intention: a tool-referenced route through perceived task automation (PTA) and an agent-referenced route through borrowed entrepreneurial competence (BEC). Digital self-efficacy (DSE) is hypothesized to moderate the conversion of both perceptual routes into intention. Solid arrows indicate hypothesized direct effects (H1–H3); the dashed arc from AI-FoMO to DEI represents its direct effect (H4); the dashed arrows originating from digital self-efficacy indicate moderating effects (H6a, H6b). H5a and H5b refer to the serial mediation paths through AI reliance and PTA/BEC.

2.4.1. AI-FoMO and AI Reliance

AI-FoMO captures workers' apprehension that they may fall behind their peers, lose competitive standing, or forfeit the rewards of AI adoption if they fail to engage with AI

tools [3,10]. According to SCT [7,8], individuals confronted with environmental demands engage in enactive coping, they take action to reduce the gap between perceived threat and current state. In AI-saturated workplaces, the most accessible coping action is direct engagement with AI tools themselves, which over time evolves into a stable behavioral pattern of AI reliance, turning to AI as a default mode of completing work tasks [11,12]. This dynamic is consistent with prior findings that workplace FoMO predicts compensatory technology engagement [6]. In the AI context, where the perceived stakes of falling behind are amplified by rapid technological change, AI-FoMO should function as a particularly potent driver of AI reliance.

It is important to acknowledge, however, that AI-FoMO need not be uniformly mobilizing. For some workers, the same apprehension may instead trigger avoidance, resistance, or stress that discourages AI engagement, consistent with the well-documented maladaptive face of FoMO [4,5]. We therefore frame H1 as a net-directional prediction: although individual responses vary, the dominant tendency in AI-saturated workplaces, grounded in SCT's enactive coping principle and prior workplace-FoMO evidence [6], is for AI-FoMO to translate into greater AI reliance. The competing avoidance pathway is revisited as a boundary condition in Section 5.4.

H1. *AI-FoMO is positively associated with AI reliance.*

2.4.2. AI Reliance and the Two Cognitive Routes

As workers increasingly rely on AI tools to complete work tasks, they accumulate direct mastery experiences of AI's task-handling capabilities [8]. Each successful instance, drafting a report with generative AI, automating data analysis, generating code or marketing copy, provides concrete evidence that AI can substitute for human effort in particular task domains. This accumulating evidence shapes a generalized cognitive appraisal of AI as a task-automating technology. Workers who heavily rely on AI come to see their work itself through an automation lens, they identify which tasks AI handles well, anticipate which future tasks could be delegated, and develop a perception that substantial portions of work can be offloaded to AI [13].

H2a. *AI reliance is positively associated with perceived task automation.*

Beyond perceiving AI as a tool, sustained AI reliance reshapes how workers perceive their own capabilities. Through repeated co-performance with AI on tasks beyond their solo capacity, the cognitive boundary between AI's competence and the worker's own competence becomes psychologically permeable, allowing AI-derived performance outcomes to be integrated into the worker's self-concept as personal capability (BEC). When AI consistently performs at high levels on tasks the worker could not perform alone, the worker observes a successful "performer" with whom they are intimately coupled. Through repeated coupling, AI's competence is psychologically borrowed into the worker's self-concept as latent personal capability for solo digital entrepreneurship. Workers high in AI reliance therefore come to perceive themselves as capable of solo entrepreneurial pursuits, believing they can compensate for deficits in experience or skill by leveraging AI tools to handle the diverse functional demands (marketing, development, operations, design) that traditionally required a founding team.

H2b. *AI reliance is positively associated with borrowed entrepreneurial competence.*

2.4.3. Cognitive Routes and Digital Commerce Entrepreneurial Intention

Digital entrepreneurial intention reflects a worker's commitment to launching a digital venture in the foreseeable future [15,21]. In established models of entrepreneurial intention, such commitment is driven jointly by perceived feasibility and perceived desirability [21,22]; perceived task automation operates on the feasibility component. A central barrier to forming such intentions is the perception that solo digital ventures require skills, time, and operational capacity beyond what an individual can muster alongside existing employment. Perceived task automation directly reduces this barrier. When workers perceive that AI can automate substantial portions of operational work, content generation, customer service, accounting, and scheduling, the cognitive cost of envisioning a viable solo venture decreases substantially. The mental simulation of "running a business while holding a job" becomes plausible because the workload is mentally pre-distributed to AI [15].

H3a. *Perceived task automation is positively associated with digital commerce entrepreneurial intention.*

The classical SCT prediction is that capability beliefs are proximal antecedents of behavioral intention: individuals form intentions to undertake actions they believe themselves competent to perform [8,22]. Borrowed entrepreneurial competence, even though its origin lies in coupling with AI, operates psychologically as a self-referential capability belief, the worker perceives that they themselves can undertake solo digital entrepreneurship through AI-augmented action. This perception removes a fundamental motivational barrier: doubt about one's own capacity. Workers who score high on BEC perceive solo digital entrepreneurship as within their reach and consequently form stronger intentions to pursue it. This logic parallels prior findings that entrepreneurial self-efficacy is one of the most robust predictors of entrepreneurial intention across cultures and contexts [16,21].

H3b. *Borrowed entrepreneurial competence is positively associated with digital commerce entrepreneurial intention.*

2.4.4. Direct Effect of AI-FoMO on Digital Commerce Entrepreneurial Intention

Beyond its indirect influence through AI reliance and downstream perceptions, AI-FoMO may retain a residual association with digital commerce entrepreneurial intention. We therefore include a direct path primarily to test whether AI reliance and the two perceptions fully account for the effect of AI-FoMO on DEI, rather than to assert an independent motivational pathway. To the extent that a direct effect remains, approach-motivation perspectives on FoMO [5] offer one plausible reading, namely that the fear of missing out can mobilize opportunity-seeking rather than only avoidance behavior. However, because a direct effect in a mediation model captures whatever covariance with AI-FoMO is not transmitted through the specified mediators, any such effect should be interpreted cautiously, as it may also reflect unmodeled mediators, common method variance, or reciprocal influence between intention and AI-FoMO under a cross-sectional design.

H4. *AI-FoMO is positively associated with digital commerce entrepreneurial intention, even after accounting for the indirect effects through AI reliance and downstream perceptions.*

2.4.5. Serial Mediation Pathways

Hypotheses H1 through H3b together imply two serial mediation pathways through which AI-FoMO shapes digital commerce entrepreneurial intention. AI-FoMO drives AI reliance (H1); AI reliance generates two distinct downstream perceptions, PTA (H2a) and

BEC (H2b), both of which in turn predict DEI (H3a, H3b). These chains constitute the central mechanistic account of how AI-related anxiety transforms into entrepreneurial intent.

H5a. *AI reliance and perceived task automation serially mediate the relationship between AI-FoMO and digital commerce entrepreneurial intention.*

H5b. *AI reliance and borrowed entrepreneurial competence serially mediate the relationship between AI-FoMO and digital commerce entrepreneurial intention.*

2.4.6. The Moderating Role of Digital Self-Efficacy

As elaborated in Section 2.3, digital self-efficacy serves as a regulatory mechanism that determines whether motivational and cognitive resources are converted into action [8]. For both perceptual routes identified above, a higher level of DSE should plausibly amplify the translation of perception into intention. Workers high in DSE possess the underlying confidence to act on opportunities they perceive: when they perceive that AI can automate work (PTA), a high DSE enables them to envision themselves orchestrating that automation in service of a venture; when they perceive themselves as competent through AI (BEC), high DSE enables them to convert that perception into committed intention. We therefore hypothesize symmetric positive moderation across both routes.

H6a. *Digital self-efficacy positively moderates the relationship between perceived task automation and digital commerce entrepreneurial intention.*

H6b. *Digital self-efficacy positively moderates the relationship between borrowed entrepreneurial competence and digital commerce entrepreneurial intention.*

3. Methodology

3.1. Research Context and Sample

South Korea provides a distinctively well-suited empirical context for examining the relationships proposed in this study for two reasons. First, South Korea is among the leading nations in enterprise AI adoption. OECD/Eurostat statistics on business AI use indicate that Korea (28% in 2022) has emerged as a leader alongside the Nordic frontrunners (Denmark, Sweden, and Finland at 24–28%), with adoption rates exceeding 25% across enterprises [23,24]. Korean knowledge workers are therefore exposed to AI tools at levels among the highest in the OECD, which ensures that workers in our sample have meaningful encounters with AI in their professional lives.

Second, South Korea features one of the most active solo and digital entrepreneurship environments among advanced economies. Solo proprietors comprise a substantial share of the Korean labor market, and platform-based and AI-augmented digital ventures have grown rapidly in recent years. This institutional and cultural backdrop makes digital commerce entrepreneurial intention a particularly meaningful and consequential outcome variable in the Korean context. Recent moderated mediation studies of Korean employees confirm the relevance of psychological mechanisms in shaping entrepreneurial intention in this setting [25], and recent JTAER work specifically documents the determinants of platform-based startup intention among Korean prospective entrepreneurs [26], reinforcing the relevance of our setting for understanding digital commerce entrepreneurial intention on emerging platforms.

Data were collected through a major Korean online survey panel between January and March 2026. The survey targeted full-time workers in South Korea who were currently

employed at the time of participation. Of the 400 invitations distributed, 340 responses were initially returned. Following standard data quality screening, including the removal of cases with straight-lining patterns, excessive missing values, and implausibly short response times, the final analytical sample comprised 328 valid responses. All participants provided informed consent, and the survey was administered in Korean.

Respondents were recruited through a professional online survey panel. Eligibility was screened at entry: only individuals who confirmed current full-time employment in South Korea proceeded to the main survey, and quota controls were applied to approximate the working-population distribution across sex and age. Prior experience with AI tools was not an eligibility requirement (see below). Quality-control exclusions, applied after data collection, removed cases exhibiting straight-lining, excessive missing values, or implausibly short completion times. An a priori power analysis supports the adequacy of the resulting sample: for the most demanding regression in the model (DEI, with up to six antecedents, including the two interaction terms), G*Power 3.1 indicates that detecting a medium effect ($f^2 = 0.15$) at $\alpha = 0.05$ with power = 0.80 requires a minimum of 98 cases, and the inverse-square-root method indicates that detecting a path coefficient as small as 0.20 at 80% power requires approximately 200 cases; our analytical sample of 328 exceeds both thresholds.

We deliberately did not restrict participation to current AI users. AI-FoMO and entrepreneurial intention are theoretically meaningful for non-users as well, and peer-relative anxiety is often most acute among those who have not yet engaged. To verify that including the 95 respondents (29.0%) without prior AI experience did not drive the findings, we included AI-usage experience among the demographic control variables in a robustness model (Section 4.5), under which the hypothesized paths remained stable in sign and significance. Re-estimating the full model on the AI-experienced subsample ($n = 233$) preserved the structure of effects (AI reliance $\rightarrow$ PTA = 0.503, AI reliance $\rightarrow$ BEC = 0.250, PTA $\rightarrow$ DEI = 0.326, BEC $\rightarrow$ DEI = 0.201, BEC $\times$ DSE = 0.106, R^2DEI = 0.486), confirming that the non-users did not drive the findings. Regarding research ethics, the study qualified for exemption from full institutional review board review as an anonymous survey of adults that collected no personally identifiable or sensitive information, under Article 13(1)(ii) of the Enforcement Rule of the Bioethics and Safety Act of the Republic of Korea; the formal statement appears in the back matter.

Sample demographics are summarized in Table 3. The sample was 62.5% male and 37.5% female, with respondents distributed across age groups: 15.5% under 30, 30.8% in their 30s, 31.7% in their 40s, and 22.0% aged 50 or above. Educational attainment was relatively high, with 86.6% of participants holding a bachelor's degree or higher. Occupationally, 55.5% worked in clerical or managerial roles, 16.8% in professional or technical roles, and 27.8% in other occupations. A majority (71.0%) reported prior experience using AI tools, and monthly income was distributed broadly across the four reported brackets.

Table 3. Sample demographics ($N = 328$).

Variable	Category	*n*	%
Sex	Male	205	62.5
	Female	123	37.5
Age	Under 30	51	15.5
	30–39	101	30.8
	40–49	104	31.7
	50 or above	72	22.0
Education	High school or below	29	8.8
	Currently in college	15	4.6
	Bachelor's degree	230	70.1
	Graduate degree	54	16.5

Table 3. *Cont.*

Variable	Category	*n*	%
Occupation	Clerical/Managerial	182	55.5
	Professional/Technical	55	16.8
	Other	91	27.8
AI Use Experience	Yes	233	71.0
	No	95	29.0
Monthly Income	Below 2M KRW (~$1400)	54	16.5
	2M–3M KRW (~$1400–2100)	92	28.0
	3M–4M KRW (~$2100–2800)	76	23.2
	Above 4M KRW (>$2800)	106	32.3

Note. Total N = 328. KRW = Korean Won.

3.2. Measures

All constructs were measured using multi-item reflective scales adapted from established sources in the literature (Table 4). Each construct was operationalized with four items rated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). The full set of measurement items is reported in the Appendix A.

AI-related fear of missing out (AI-FoMO) was measured with four items adapted from Przybylski et al. [9] and Elhai et al. [4], with content contextualized from social media to AI engagement. *AI reliance* was measured with four items adapted from the IS continuance and habit literature [11,27] and from recent work on AI workplace reliance [12]. *Perceived task automation (PTA)* was measured with four items adapted from Brougham and Haar's [13] STARA awareness scale.

Borrowed entrepreneurial competence (BEC) is a new construct proposed in this study. We developed four items by drawing on Bandura's [8] theoretical framework of vicarious experience and adapting De Noble et al.'s (1999) [28] entrepreneurial self-efficacy items, with each item explicitly anchoring the capability belief in AI-coupling (e.g., "With the support of AI tools, I feel capable of performing key entrepreneurial tasks"; "AI tools enable me to handle business functions that I could not manage alone"). *Digital self-efficacy (DSE)* was measured with four items adapted from Compeau and Higgins [18] and Marakas et al. [19]. *Digital entrepreneurial intention (DEI)* was measured with four items adapted from Liñán and Chen's (2009) [21] Entrepreneurial Intention Questionnaire.

All items were originally developed in English and translated into Korean using a back-translation procedure [29]. The reliability and validity properties of the measurement model are reported in Section 4.1.

Table 4. Measurement scales and sources.

Construct	Items	Primary Source(s)
AI-FoMO	4	Deng et al. [3]; Li [10]; Przybylski et al. [9]
AI Reliance	4	Tang et al. [12]; Wu et al. [30]; Limayem et al. [11]
Perceived Task Automation	4	Brougham and Haar [13]
Borrowed Entrep. Competence	4	Proposed in this study; Bandura [8]; De Noble et al. [28]; informed by Newman et al. [16]
Digital Self-Efficacy	4	Ulfert-Blank and Schmidt [31]; Paredes-Aguirre et al. [32]; Compeau and Higgins [18]
Digital Comm. Entrep. Intention	4	Liñán & Chen (2009) [21]

Note. All items used a 7-point Likert scale. Item-level outer loadings and reliability/validity statistics are reported in Section 4.1 (Table 5).

3.3. Common Method Bias: Procedural Remedies

Because all constructs were measured from a single source (self-report) at one point in time, common method bias (CMB) was a potential concern. We applied two complementary procedures [33,34]. First, we conducted Harman's single-factor test by entering all measurement items into an unrotated principal components analysis. The first extracted factor accounted for 36.53% of the total variance, well below the conventional 50% threshold, indicating that no single factor dominated the measured variance.

Second, following Kock [34], we computed full collinearity variance inflation factors (VIFs) by regressing each construct on all others. All VIF values ranged between 1.12 and 2.06, comfortably below the recommended threshold of 3.3 for ruling out common method effects. Together, these two diagnostics suggest that common method bias was not a substantive threat to the validity of our findings.

3.4. Analytical Procedure

We tested the proposed model using partial least squares structural equation modeling (PLS-SEM) implemented in SmartPLS 4.0 [35]. PLS-SEM was selected for three reasons. First, the model includes a newly proposed construct (BEC) and complex serial mediation paths, which makes a prediction-oriented variance-based approach more appropriate [36,37]. Second, PLS-SEM imposes minimal distributional assumptions. Third, PLS-SEM efficiently handles models that combine mediating and moderating relationships.

Following standard PLS-SEM practice [36,37], we conducted a two-stage analysis. In the first stage, we evaluated the measurement model by examining indicator reliability, construct reliability (Cronbach's α and composite reliability), convergent validity (AVE), and discriminant validity (HTMT ratios). In the second stage, we evaluated the structural model by examining path coefficients, the explained variance (R^2) of endogenous constructs, effect sizes (f^2), and predictive relevance (Q^2). Path coefficient significance was assessed using bootstrapping with 5000 subsamples [38]. Moderation hypotheses (H6a, H6b) were tested using the two-stage approach to construct latent interaction terms.

4. Results

4.1. Measurement Model Assessment

Following standard PLS-SEM practice [36,37], we first evaluated the measurement model. Outer loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) for all six constructs are reported in Table 5. Most loadings exceeded the conventional 0.70 cutoff. The DEI items showed somewhat lower loadings (0.600–0.755), with DEI4 ('I have seriously considered starting a digital business') exhibiting the lowest loading (0.600). We retained all four DEI items based on three considerations. First, all loadings exceeded the 0.50 minimum acceptable threshold for newly applied or contextually adapted scales [36]. Second, removing the lower-loading items did not improve construct reliability or AVE: a sensitivity analysis showed that dropping DEI4 yielded only marginal AVE improvement ($\Delta = 0.032$) while reducing content coverage of the construct. Third, the four items collectively capture distinct facets of intention strength, ranging from active commitment (DEI1) to deliberation (DEI4), which is theoretically meaningful for a construct that necessarily encompasses both nascent and crystallized intentions [21]. Construct reliability ($\alpha = 0.813$, CR = 0.877) and convergent validity (AVE = 0.644) remained well above conventional thresholds. All other constructs likewise demonstrated acceptable internal consistency (Cronbach's α ranging from 0.871 to 0.916; CR ranging from 0.918 to 0.941) and convergent validity (AVE ranging from 0.756 to 0.798), all exceeding the conventional thresholds [39].

Table 5. Measurement model: Outer loadings, reliability, and convergent validity.

Construct	Item	Loading	α	CR	AVE
AI-FoMO	FoMO1	0.822	0.906	0.934	0.779
	FoMO2	0.828			
	FoMO3	0.824			
	FoMO4	0.728			
AI Reliance	AIR1	0.851	0.888	0.924	0.756
	AIR2	0.845			
	AIR3	0.865			
	AIR4	0.652			
Perc. Task Automation	PTA1	0.792	0.897	0.928	0.763
	PTA2	0.837			
	PTA3	0.711			
	PTA4	0.847			
Borrowed Entrep. Competence	BEC1	0.764	0.916	0.941	0.798
	BEC2	0.828			
	BEC3	0.826			
	BEC4	0.818			
Digital Self-Efficacy	DSE1	0.884	0.901	0.929	0.765
	DSE2	0.862			
	DSE3	0.885			
	DSE4	0.836			
Digital Comm. Entrep. Intention	DEI1	0.755	0.813	0.877	0.644
	DEI2	0.639			
	DEI3	0.663			
	DEI4	0.600			

Note. α = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted.

Discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio of correlations [40]. As shown in Table 6, all HTMT values were below the conservative 0.85 threshold, with the highest value at 0.689 (PTA–DEI), confirming discriminant validity.

Table 6. Discriminant validity: HTMT ratios.

	AIR	BEC	DEI	FoMO	DSE	PTA
AI Reliance (AIR)						
Borrowed Entrep. Comp. (BEC)	0.322					
Digital Entrep. Intent. (DEI)	0.649	0.603				
AI-FoMO (FoMO)	0.431	0.650	0.618			
Digital Self-Efficacy (DSE)	0.021	0.300	0.201	0.253		
Perc. Task Automation (PTA)	0.586	0.514	0.665	0.464	0.060	

Note. HTMT = Heterotrait–monotrait ratio. All values were below the 0.85 threshold [40].

Discriminant validity was further confirmed with the Fornell–Larcker criterion (Table 7), and indicator-level collinearity was assessed via outer VIFs (Table 8).

Table 7. Discriminant validity: Fornell–Larcker criterion.

	FoMO	AIR	PTA	BEC	DSE	DEI
FoMO	0.883					
AIR	0.391	0.869				
PTA	0.430	0.531	0.873			
BEC	0.594	0.291	0.470	0.894		
DSE	0.230	0.001	0.046	0.277	0.875	
DEI	0.529	0.565	0.602	0.524	0.168	0.803

Table 8. Indicator collinearity (outer VIF).

Indicator	VIF	Indicator	VIF
Fear1	3.26	Ent_Cap1	2.72
Fear2	3.27	Ent_Cap2	3.05
Fear3	2.38	Ent_Cap3	3.34
Fear4	2.30	Ent_Cap4	2.92
AI_dep1	3.88	Self_Eff1	3.32
AI_dep2	4.80	Self_Eff2	2.68
AI_dep3	3.54	Self_Eff3	3.03
AI_dep4	1.42	Self_Eff4	2.26
Task_Aut1	2.73	Ent_Int1	1.31
Task_Aut2	2.73	Ent_Int2	1.99
Task_Aut3	2.30	Ent_Int3	2.00
Task_Aut4	2.62	Ent_Int4	1.98

Note. VIF computed for each indicator against the remaining indicators of its construct. All values were below the 5.0 threshold (highest = AI_dep2 = 4.80), indicating no problematic indicator collinearity.

4.2. Common Method Bias

As described in Section 3.3, two complementary diagnostics were applied. Harman's single-factor test indicated that the first extracted factor accounted for 36.53% of the total variance, and full collinearity VIF values for all constructs ranged between 1.12 and 2.06 [34]. Both diagnostics indicate that common method bias did not pose a substantive threat to the validity of our findings.

4.3. Structural Model Assessment

We evaluated the structural model in terms of explained variance (R^2), effect sizes (f^2), and predictive relevance (Q^2) [37]. Results are summarized in Table 9. The model accounted for a substantial share of variance in digital commerce entrepreneurial intention ($R^2 = 0.543$) and meaningful variance in perceived task automation ($R^2 = 0.282$). The Q^2 values reported here are blindfolding-based (cross-validated redundancy); all were positive, confirming the in-sample predictive relevance of the model [41,42]. As a robustness check, we additionally conducted a PLSpredict analysis: Q^2predict was positive for AI reliance (0.147), BEC (0.122), and PTA (0.134), whereas DEI returned a negative Q^2predict (−0.109), indicating limited out-of-sample predictive power for the final outcome construct. As an approximate measure of overall model fit, the standardized root mean square residual (SRMR) for the saturated model was 0.060, below the 0.08 threshold (the estimated-model SRMR was 0.140; for complex PLS models that include interaction terms, the saturated-model SRMR

is generally regarded as the more relevant fit index). Effect-size analysis indicates that the strongest contributions to DEI came from AI reliance ($f^2 = 0.122$), PTA ($f^2 = 0.111$), and BEC ($f^2 = 0.050$); the two interaction terms contributed small effects (BEC × DSE $f^2 = 0.017$; PTA × DSE $f^2 = 0.010$).

Table 9. Structural model: Explained variance and predictive relevance.

Endogenous Construct	R^2	Q^2	Interpretation
AI Reliance	0.153	0.136	Predictive relevance confirmed
Perceived Task Automation	0.282	0.257	Predictive relevance confirmed
Borrowed Entrep. Competence	0.085	0.069	Predictive relevance confirmed
Digital Comm. Entrep. Intention	0.543	0.425	Substantial explanatory power

Note. $Q^2 > 0$ indicates predictive relevance [37].

One result warrants explicit interpretation. AI reliance explains a comparatively small share of the variance in borrowed entrepreneurial competence ($R^2 = 0.085$), in contrast to its stronger explanation of perceived task automation ($R^2 = 0.282$). We read this asymmetry as theoretically informative rather than as a weakness of the construct. It indicates that habitual AI use is a necessary behavioral substrate for borrowed competence but not its dominant determinant: the internalization of AI-coupled performance into the self-concept plausibly depends on additional, unmodeled factors, including individual differences in susceptibility to competence borrowing, the sophistication and autonomy of the AI tools used, task characteristics, and prior entrepreneurial exposure. Importantly, despite this modest R^2, the BEC-mediated serial indirect path remained statistically significant (see Section 4.4), so the pathway is supported while being understood as one of several routes to borrowed competence rather than the exclusive one. We identify the determinants of borrowed competence as a priority for future research.

4.4. Hypothesis Testing

Path coefficients, t-statistics, and *p*-values for all hypothesized relationships are reported in Table 10 and summarized graphically in Figure 2. Significance was assessed using percentile bootstrap confidence intervals based on 5000 subsamples.

Table 10. Hypothesis testing results.

Hyp.	Path	β	SE	t	*p*	Result
H1	AI-FoMO → AI Reliance	0.391	0.046	8.329	<0.001	Supported
H2a	AI Reliance → PTA	0.531	0.041	13.097	<0.001	Supported
H2b	AI Reliance → BEC	0.291	0.052	5.582	<0.001	Supported
H3a	PTA → DEI	0.291	0.050	5.769	<0.001	Supported
H3b	BEC → DEI	0.204	0.053	3.826	<0.001	Supported
H4	AI-FoMO → DEI (direct)	0.160	0.056	2.873	0.006	Supported
—	AI Reliance → DEI (direct)	0.288	0.052	5.539	<0.001	Supported
—	DSE → DEI (direct)	0.057	0.038	1.490	0.105	n.s.
H5a	FoMO → AIR → PTA → DEI	0.060	0.015	4.065	<0.001	Supported
H5b	FoMO → AIR → BEC → DEI	0.023	0.009	2.516	0.012	Supported
H6a	DSE × PTA → DEI	−0.077	0.045	1.711	0.109	Not supported
H6b	DSE × BEC → DEI	0.105	0.043	2.413	0.025	Supported

Note. β = standardized path coefficient; SE = standard error. Bootstrapping with 5000 subsamples. n.s. = not significant.

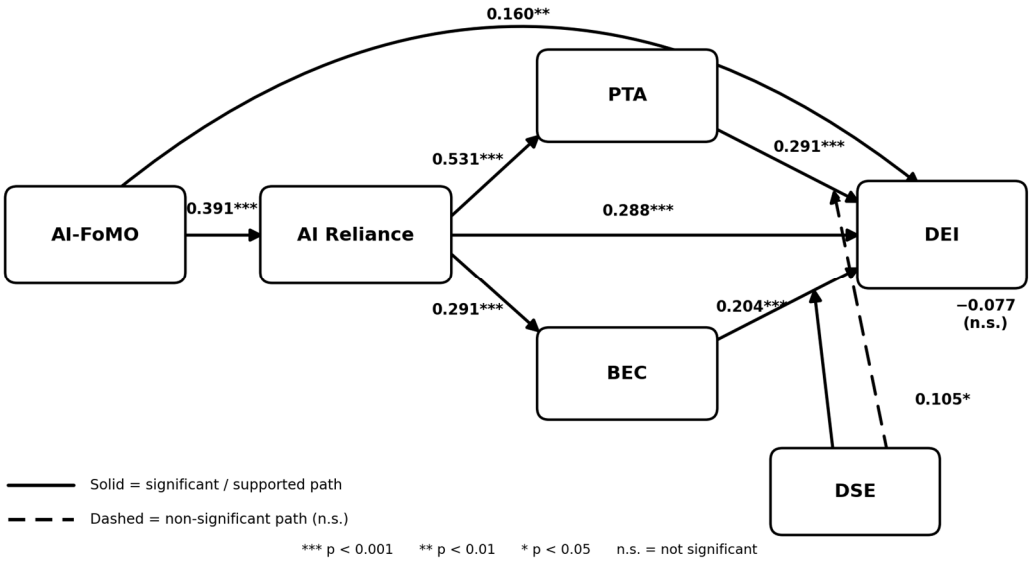


Figure 2. Structural model with estimated path coefficients. Standardized coefficients shown; significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; n.s. = not significant. Solid paths are statistically significant; the dashed path (H6a) is non-significant.

Direct effects: AI-FoMO exerted a strong positive effect on AI reliance ($\beta = 0.391$, $p < 0.001$), supporting H1. AI reliance predicted both PTA ($\beta = 0.531$, $p < 0.001$) and BEC ($\beta = 0.291$, $p < 0.001$), supporting H2a and H2b. Both perceptions then predicted DEI (PTA: $\beta = 0.291$, $p < 0.001$; BEC: $\beta = 0.204$, $p < 0.001$), supporting H3a and H3b. AI-FoMO retained a significant direct effect on DEI ($\beta = 0.160$, $p = 0.006$), supporting H4. AI reliance additionally exerted a significant direct effect on DEI ($\beta = 0.288$, $p < 0.001$), over and above its two indirect routes; this direct AI reliance → DEI path is part of the estimated structural model (Table 10).

Serial mediation effects: Both serial mediation paths were significant. The PTA route yielded an indirect effect of $\beta = 0.060$ ($p < 0.001$), and the BEC route yielded $\beta = 0.023$ ($p = 0.012$), supporting H5a and H5b. The PTA-mediated indirect effect was approximately 2.6 times larger than the BEC-mediated indirect effect ($0.060/0.023 \approx 2.61$), suggesting that the tool-referenced perception is the more potent transmission channel between AI reliance and entrepreneurial intention.

Moderation effects: An asymmetric finding: The two moderation hypotheses, which we expected to yield symmetric positive effects, instead revealed an asymmetric pattern. H6a was *not supported* ($\beta = -0.077$, $p = 0.109$); the interaction term was non-significant and pointed in the opposite direction from our prediction. In contrast, H6b *was supported* ($\beta = 0.105$, $p = 0.025$). To probe the H6b interaction, we conducted simple slopes analysis [43] with bootstrap-based significance testing (5000 resamples). At low DSE (-1 SD), the BEC → DEI slope was non-significant (slope = 0.099, $p = 0.099$), whereas at high DSE (+1 SD), the slope was strong and highly significant (slope = 0.309, $p < 0.001$), and the difference between these two slopes was itself statistically significant (Δslope = 0.210, $p = 0.025$). This pattern indicates that BEC translates into entrepreneurial intention only when workers also possess broader digital self-efficacy. The interaction is visualized in Appendix B (Figure A1). The asymmetric pattern, which was not anticipated by our initial theorization, carries direct implications for understanding how self-efficacy interacts with different types of AI-induced perceptions, and we develop its interpretation in Section 5.2.

Because the difference between a significant and a non-significant coefficient is not itself a test of difference, we additionally tested whether the two interaction coefficients differed from each other. Using the bootstrap distribution of the difference between the BEC

and DEI moderation and the PTA and DEI moderation (5000 subsamples), which accounts for the covariance between the two estimates, the difference was $\Delta\beta = 0.182$, with a 95% percentile confidence interval of [0.021, 0.313] that excludes zero, and a two-tailed bootstrap $p = 0.031$. This direct comparison indicates that the asymmetry reflects a genuine difference in how digital self-efficacy regulates the two routes rather than sampling variability across two separately judged significance levels.

In sum, nine of the ten hypotheses were supported, while H6a was not. The full proposed mechanism, AI-FoMO mobilizes AI reliance, which generates two distinct cognitive routes that shape DEI, was empirically substantiated. The unexpected asymmetric moderation finding constitutes a theoretically generative outcome of the present study.

4.5. Robustness Check: Control Variables

As a robustness check, we re-estimated the model with demographic variables (gender, age, education, occupation, income, and AI-usage experience) included as controls predicting DEI. The signs and significance of the hypothesized relationships were largely unchanged: AI-FoMO increased AI reliance ($\beta = 0.391$, $p < 0.001$), AI reliance positively affected PTA ($\beta = 0.531$, $p < 0.001$) and BEC ($\beta = 0.291$, $p < 0.001$), and both PTA ($\beta = 0.351$, $p < 0.001$) and BEC ($\beta = 0.208$, $p < 0.001$) predicted DEI. The moderating effects followed the same pattern as in the main model, with the PTA route interaction non-significant (DSE $\times$ PTA: $\beta = -0.079$, $p = 0.066$) and the BEC route interaction positive and significant (DSE $\times$ BEC: $\beta = 0.123$, $p = 0.003$). These results indicate that the findings are robust to the inclusion of demographic controls.

We additionally conducted a multigroup analysis (PLS-MGA) contrasting respondents with prior AI experience ($n = 233$) and those without ($n = 95$). None of the structural paths differed significantly between the two groups (all $p > 0.20$), indicating that the hypothesized mechanism is invariant across AI-experience status; the smaller size of the no-experience group ($n = 95$) nonetheless warrants caution in interpreting the group comparison.

5. Discussion

5.1. Summary of Findings

Our findings substantiate the central thesis of this study: AI-related fear of missing out is not merely a maladaptive emotional state but a generative force that mobilizes workers toward proactive, opportunity-seeking behavior. Specifically, AI-FoMO drives AI reliance (H1), which in turn produces two analytically distinct cognitive routes, PTA (H2a) and BEC (H2b), both of which translate into digital commerce entrepreneurial intention (H3a, H3b). AI-FoMO also retains a direct motivational effect on DEI beyond the mediated routes (H4), and both serial mediation paths were significant (H5a, H5b). The PTA route was approximately 2.6 times stronger than the BEC route, identifying perceived task automation as the more potent transmission channel from AI reliance to entrepreneurial intention. The most theoretically generative finding, however, was the asymmetric pattern of moderation by digital self-efficacy: against our initial expectation of symmetric positive moderation, DSE amplified the BEC route (H6b supported) but not the PTA route (H6a not supported).

5.2. Theoretical Contributions

This study makes four theoretical contributions. *First*, we reframe AI-FoMO as a Janus-faced construct that produces approach- as well as avoidance-oriented behaviors. Whereas the dominant FoMO literature has emphasized maladaptive outcomes [4,5], our findings show that AI-FoMO can mobilize workers toward agentic, career-relevant action, most notably, the formation of digital commerce entrepreneurial intention. This reframing extends recent calls to reconceptualize FoMO as a multifaceted motivational state [5]

and identifies AI-FoMO as a particularly potent driver because it concerns the loss not of social experiences, but of *competence dividends*, productivity, career advantages, and entrepreneurial opportunities perceived to flow from AI adoption.

Second, we propose and empirically support borrowed entrepreneurial competence (BEC) as a new construct that captures how human–AI coupling reshapes workers' self-perceived capability for solo digital entrepreneurship. BEC extends Bandura's [8] classical concept of vicarious experience to the human–AI context, replacing distant observation of similar others with intimate co-performance in which the worker is themselves a co-author of each AI-mediated output. Through repeated coupling, the cognitive boundary between AI's competence and the worker's own competence becomes psychologically permeable, allowing AI-derived performance outcomes to be integrated into the worker's self-concept as personal capability. This conceptualization offers a parsimonious account of an important yet understudied phenomenon, the fact that workers often feel *more capable* after sustained AI use, even on tasks they could not perform unaided, and provides a conceptual scaffold for future research on AI's transformative effects on worker self-concept.

Third, and most generative, our findings reveal an *asymmetric moderation pattern* by digital self-efficacy that refines the agentic premise of social cognitive theory. Although classical SCT [8] might predict that self-efficacy uniformly amplifies the perception-to-intention link, our results indicate that self-efficacy operates with greater specificity. The simple slopes analysis is particularly revealing: at low levels of digital self-efficacy, the BEC $\rightarrow$ DEI slope was statistically indistinguishable from zero (slope = 0.099, $p = 0.099$), whereas at high digital self-efficacy, the slope was strong and highly significant (slope = 0.309, $p < 0.001$), with the difference between these slopes itself reaching significance (Δslope = 0.210, $p = 0.025$). In other words, perceiving oneself as competent through AI does not, on its own, generate entrepreneurial intention; the perception must be coupled with broader digital self-efficacy to be converted into committed intent. The PTA route, in contrast, operated robustly across all levels of digital self-efficacy, with the interaction term even pointing in the opposite (negative) direction from our prediction.

We propose the following theoretical interpretation. Self-efficacy beliefs and BEC are both *self-referential cognitions* occupying the same psychological domain, beliefs about the self as an agent capable of action. When these self-referential cognitions align, they engage with each other to amplify intention: the worker who believes "I can act capably through AI" (BEC) requires the broader confidence "I can navigate digital environments effectively" (DSE) to translate that capability belief into committed intention. PTA, in contrast, concerns an external object, AI's automation capability, rather than the self. As a tool-referenced cognition, PTA operates through a different cognitive route that does not engage with the self-efficacy system. The marginal negative interaction we observed ($\beta = -0.077$, $p = 0.109$) further suggests that when both PTA and DSE are high, workers may even discount the relevance of automation perceptions, perhaps because confident workers attribute capability to themselves rather than to the tool. This finding suggests that the regulatory role of self-efficacy in SCT is conditional on the *self-referential nature* of the cognition being regulated. Self-efficacy does not amplify all perceptions equally; it engages selectively with cognitions about the self, while bypassing or even competing with cognitions about external technological objects. This refinement carries direct implications for how scholars theorize and test self-efficacy moderation in technology-rich settings, and provides a more nuanced reading of Bandura's agentic premise in the human–AI era.

Fourth, our framework contributes to the *platform innovation literature* by relocating part of the explanatory load from supply-side platform design to user-side cognitive transformation. Existing platform innovation research has emphasized how platform architectures, modular interfaces, network effects, and ecosystem orchestration enable new

venture creation [15]. Our findings introduce a complementary, *psychologically endogenous* mechanism: as *AI-enabled platform services* become deeply embedded in workers' routines, sustained co-performance with these services psychologically transfers AI's competence into workers' self-concepts (BEC), thereby expanding the population of individuals who perceive themselves as capable of becoming platform-based entrepreneurs. In this view, generative AI on digital platforms operates not only as productivity infrastructure but also as a *supply-side amplifier of digital commerce entrepreneurship* through cognitive rather than purely technical channels. This reframes platform innovation as a co-evolutionary process between AI-enabled services and user-side capability beliefs, in which the boundaries between platform users, platform-based service consumers, and platform-based entrepreneurs become increasingly cognitive rather than structural.

5.3. Practical Implications

Because this study tested no intervention, the recommendations below are design-informing inferences anchored to specific results rather than evaluated prescriptions. Two results carry the most direct guidance. First, because the tool-referenced route carries the stronger serial pathway (its indirect effect is roughly 2.6 times that of the agent-referenced route), demonstrating concrete task automation is the most efficient lever for initial intention formation. Second, because borrowed competence converts into intention only at higher digital self-efficacy (the simple slope is significant at +1 SD but not at −1 SD), capability-belief interventions should be paired with digital-skill and self-efficacy building rather than deployed alone.

These uses also raise an ethical consideration. Our finding that AI-FoMO can be channeled into constructive engagement should not be read as a license to amplify anxiety as a motivational lever. Deliberately heightening workers' fear of falling behind risks chronic stress, burnout, and coercive adoption climates, and may disadvantage those with fewer resources to respond. The responsible application is to channel pre-existing anxiety into low-stakes mastery opportunities and capability building, not to manufacture it; organizations and platform designers should weigh these well-being trade-offs explicitly when acting on the mechanisms documented here.

Our findings carry implications for organizations, educators, and policymakers concerned with workforce adaptation in the AI era. For *organizations*, the results suggest that workers' anxiety about AI is not solely a problem to be managed but also a resource that can be channeled into productive engagement. Rather than seeking to reduce AI-related anxiety per se, organizations may benefit from creating structures that translate this anxiety into constructive AI engagement, for example, by providing accessible, low-stakes opportunities for workers to develop habitual AI use. Organizations should be aware that sustained AI engagement may shift worker self-perception toward solo capability.

For *educators and policymakers* concerned with entrepreneurship support, our asymmetric moderation finding offers a concrete and actionable insight. Simply exposing workers to AI tools and encouraging adoption may produce intention-formation through the tool-perception route (PTA), but the more sustainable conversion of intention into committed entrepreneurial behavior likely requires *self-referential capability beliefs* (BEC) coupled with broader digital self-efficacy. Entrepreneurship training programs in the AI era should therefore go beyond demonstrating AI's capabilities and explicitly cultivate participants' beliefs in their own capability to act through AI.

Beyond organizational and educational settings, our findings carry implications for *broader workforce development and digital skills initiatives*. Programs concerned with workforce readiness for the AI era often focus on technical access, digital infrastructure, and basic AI literacy. Our results suggest that these initiatives, while necessary, are not sufficient. The

capability-conversion mechanism we document, in which AI-related anxiety mobilizes AI engagement and reshapes workers' self-perceived capability for digital ventures, indicates that policy interventions should also attend to the *psychological infrastructure* of digital adoption: how workers internalize AI-derived performance into their own sense of capability, and how broader digital self-efficacy gates this conversion. National AI strategies and digital workforce development programs may therefore benefit from integrating self-efficacy-building components, peer learning communities, and structured opportunities for workers to translate AI exposure into self-referential capability beliefs that support digital entrepreneurship and small-venture formation. This is particularly relevant for economies pursuing AI-driven entrepreneurial ecosystems, where the conversion of widespread AI adoption into bottom-up venture creation depends not only on technological infrastructure, but also on the cognitive readiness of the workforce.

Specifically for digital platforms and emerging-technology ecosystems, the mechanisms documented here speak to platform operators, digital commerce ecosystem designers, and platform-based entrepreneurship intermediaries. The capability-conversion mechanism we identify suggests that platforms positioning themselves as launch infrastructure for AI-supported solo digital commerce ventures, including AI-assisted e-commerce storefronts, platform-mediated service marketplaces, and creator-economy infrastructures, can amplify supply by deliberately scaffolding *borrowed capability beliefs* in prospective entrepreneurs. Concretely, this implies designing onboarding flows, in-platform AI tools, and community structures that frame AI as enabling personal entrepreneurial capability rather than merely as automation infrastructure. Our findings further suggest that platform operators concerned with the supply of digital commerce ventures should attend to two distinct cognitive levers: a tool-referenced lever (demonstrating concrete operational automation) and an agent-referenced lever (building the worker's sense that they personally can launch a venture through AI), recognizing that the latter is gated by broader digital self-efficacy.

These findings also speak directly to the design of *AI-enabled platform services* more broadly. Generative AI features deployed on digital platforms (such as algorithmic recommendation, content generation, automated customer interaction, and predictive analytics) are typically evaluated by their efficiency or accuracy. Our results suggest a complementary criterion: the extent to which prolonged engagement with these services builds *user-side capability beliefs* that translate into new entrepreneurial supply on the platform. Platform innovation strategies oriented toward expanding the venture base, therefore, should not treat AI tools as productivity utilities alone, but as *cognitive infrastructure* that gradually transforms ordinary platform users into prospective platform-based entrepreneurs. Practically, this implies investing in AI service experiences in which users actively co-perform with AI rather than passively consume its outputs, designing transparency and provenance signals that allow users to internalize AI-supported outputs as their own work, and aligning onboarding journeys with the digital self-efficacy regulator we identified, so that the agent-referenced capability route is fully activated.

5.4. Limitations and Future Research

Several limitations should be noted. *First*, our data are cross-sectional and based on self-reports collected at a single point in time. Although the proposed serial mediation model is theoretically directional and our two-stage diagnostic procedures suggested that common method bias is not a substantive threat, cross-sectional data preclude causal inference. Future research using longitudinal or experimental designs would strengthen the causal interpretation of the AI-FoMO $\rightarrow$ AI reliance $\rightarrow$ perception $\rightarrow$ intention chain. *Second*, our sample comprised Korean workers, drawn from a context characterized by high enterprise AI adoption and an active solo-entrepreneurship environment. While

these features make Korea a particularly suitable empirical setting for the present research questions, they also constrain the generalizability of our findings. Future research should test the proposed model in diverse cultural and institutional contexts, especially those that differ in AI adoption levels, regulatory environments, or entrepreneurial ecosystems.

Beyond these two design limitations, several boundaries of construct measurement and scope should be acknowledged. First, although the square-root-of-AVE and HTMT criteria support discriminant validity, our data cannot fully separate borrowed entrepreneurial competence from entrepreneurial self-efficacy measured in an AI context at the item level; a direct incremental-validity test against an established entrepreneurial self-efficacy scale, ideally combined with a manipulation of AI availability, is an essential next step for validating the construct. Second, and relatedly, we adopted a validated AI-FoMO scale but did not include a parallel AI anxiety measure, so we cannot empirically rule out overlap between AI-FoMO and general AI anxiety; future work should model the two jointly to establish incremental predictive validity. Third, as noted in Section 4.3, AI reliance explains only a modest share of borrowed competence, implying unmodeled antecedents (individual susceptibility to competence borrowing, tool sophistication, task characteristics) that future designs should measure directly. Fourth, the survey did not capture work tenure or job autonomy, which may condition the proposed relationships; incorporating these is a useful extension. Finally, the significant but small direct effect of AI-FoMO on intention should be read as a residual rather than as firm evidence of an independent approach-motivation pathway, given the possibility of unmodeled mediators, common method variance, or reciprocal causation.

More broadly, our model isolates the cognitive antecedents of digital commerce entrepreneurial intention, specifically how AI engagement reshapes task-referenced and self-referenced capability perceptions. These cognitive routes operate within a wider constellation of determinants that govern whether intention forms and ultimately converts into venture creation, including individual risk propensity, access to financial resources, the breadth and quality of personal and professional networks, and personal goals and opportunity costs. The mechanism we document should therefore be understood as one psychologically proximal pathway within this larger system rather than a complete account of entrepreneurial decision-making in the AI era. Establishing how AI-induced capability beliefs interact with these dispositional, social, and resource-based factors, and how the relative weight of each shifts as AI diffusion deepens, is an important agenda for follow-on research and for the design of policies intended to support entrepreneurial activity in the age of AI.

6. Conclusions

This study offers a mechanistic account of how AI-related anxiety transforms into entrepreneurial intent. AI-FoMO mobilizes workers into AI reliance, which in turn shapes two analytically distinct perceptions, perceived task automation and borrowed entrepreneurial competence, that together convert anxiety into the intention to launch a digital venture. By introducing borrowed entrepreneurial competence as a new construct, we capture how sustained human–AI coupling reshapes workers' self-perceived capability for solo entrepreneurship: AI's competence is psychologically borrowed into the worker's self-concept as personal capability. By documenting an asymmetric moderation pattern in which digital self-efficacy amplifies only the agent-referenced route, we offer a refinement to the agentic premise of social cognitive theory: self-efficacy regulates perception-to-intention conversion selectively, engaging with self-referential cognitions but bypassing tool-referential cognitions. Together, these findings reframe AI-FoMO from a purely maladaptive emotion into a generative force for entrepreneurial action and clarify the cognitive architecture

through which AI use reshapes workers' career-relevant self-concept. As AI continues to diffuse through the workplace, understanding how workers' anxiety, dependence, and self-perception interact to shape their professional trajectories will become an increasingly central question for researchers, organizations, and policymakers alike.

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Institutional Review Board Statement: This study was conducted in the Republic of Korea. It was a fully anonymous online survey of adult participants and did not collect any personally identifiable information or sensitive personal information as defined under Article 23 of the Personal Information Protection Act of the Republic of Korea. The study meets the conditions for exemption from full IRB review set forth in Article 13(1)(ii) of the Enforcement Rule of the Bioethics and Safety Act of the Republic of Korea. The study was conducted in accordance with the Declaration of Helsinki (1975, revised 2013).

Informed Consent Statement: Informed consent was obtained electronically from all participants prior to their participation. Before accessing the survey, participants were presented with a consent statement describing the study's purpose, the voluntary and anonymous nature of participation, the academic use of the data, and their right to withdraw at any time. Only respondents who indicated affirmative consent proceeded to the survey.

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The dataset is not publicly available because the participants—adult workers in South Korea who responded to an anonymous online survey—consented to the use of their responses for academic research conducted by the research team, and public release of the dataset was not within the scope of the informed consent provided at the time of data collection.

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Appendix A. Measurement Items

All items used a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). Items were originally drafted in English and translated into Korean using a back-translation procedure [29]. Each construct below provides its conceptual definition and full item wording; source citations are consolidated in Table 4 to avoid duplication.

Appendix A.1. AI-Related Fear of Missing Out (FoMO)

Definition A1. *Workers' apprehension that they may fall behind, lose competitive standing, or forfeit opportunities if they fail to engage with AI tools at the same level as their peers.*

Table A1. AI-related fear of missing out (AI-FoMO) measurement items.

Code	Item
FoMO1	I feel uneasy when I think I am not keeping up with AI developments relevant to my work.
FoMO2	I worry that others may gain advantages by using AI tools that I do not use.
FoMO3	I feel pressure to stay informed about AI technologies used in my field.
FoMO4	I feel anxious when I see others benefiting from AI tools that I am not using.

Appendix A.2. AI Reliance (AIR)

Definition A2. *A behavioral pattern in which workers habitually turn to AI tools as a default mode of completing work tasks, integrating AI into their standard workflows.*

Table A2. AI reliance measurement items.

Code	Item
AIR1	I regularly use AI tools to complete important work tasks.
AIR2	When facing a task, I tend to turn to AI tools before other resources.
AIR3	I incorporate AI tools as a standard part of my work process.
AIR4	I depend on AI tools to improve the efficiency of my work tasks.

Appendix A.3. Perceived Task Automation (PTA)

Definition A3. *Workers' cognitive appraisal that AI is capable of automating substantial portions of their current work tasks.*

Table A3. Perceived task automation (PTA) measurement items.

Code	Item
PTA1	Many of my current work tasks can be automated using AI technologies.
PTA2	AI systems can perform tasks that I currently handle myself.
PTA3	A substantial portion of routine work can be replaced by AI.
PTA4	AI is capable of taking over tasks that require human effort in my job.

Appendix A.4. Borrowed Entrepreneurial Competence (BEC)

Definition A4. *A worker's perception that they personally possess the capability to launch and operate a digital venture, formed through accumulated experience of co-performing with AI tools on tasks beyond the worker's solo capacity.*

Table A4. Borrowed entrepreneurial competence (BEC) measurement items.

Code	Item
BEC1	With the support of AI tools, I feel capable of performing key entrepreneurial tasks.
BEC2	AI tools enable me to handle business functions that I could not manage alone.
BEC3	I can compensate for my lack of experience by using AI tools in business activities.
BEC4	My ability to start and run a business is strengthened by AI technologies.

Appendix A.5. Digital Self-Efficacy (DSE)

Definition A5. *Workers' confidence in their ability to learn, navigate, troubleshoot, and produce value using digital technologies in general work contexts.*

Table A5. Digital self-efficacy (DSE) measurement items.

Code	Item
DSE1	I am confident in my ability to learn new digital technologies.
DSE2	I can effectively use digital tools to accomplish work-related tasks.
DSE3	I can troubleshoot problems when using digital systems.
DSE4	I feel confident in producing outcomes using digital technologies.

Appendix A.6. Digital Commerce Entrepreneurial Intention (DEI)

Definition A6. *A worker's commitment to undertake the founding and operation of a digital commerce venture, including platform-based, e-commerce, and digital service ventures, in the foreseeable future.*

Table A6. Digital commerce entrepreneurial intention (DEI) measurement items.

Code	Item
DEI1	I am determined to start a digital business in the future.
DEI2	My professional goal is to become a digital entrepreneur.
DEI3	I intend to engage in digital entrepreneurial activities.
DEI4	I have seriously considered starting a digital business.

Appendix B. Interaction Plots

To visualize the asymmetric moderation pattern reported in Section 4.4 (H6a, H6b), we plotted the simple slopes of perceived task automation (PTA) and borrowed entrepreneurial competence (BEC) on digital commerce entrepreneurial intention (DEI) at low (−1 SD) and high (+1 SD) levels of digital self-efficacy (DSE).

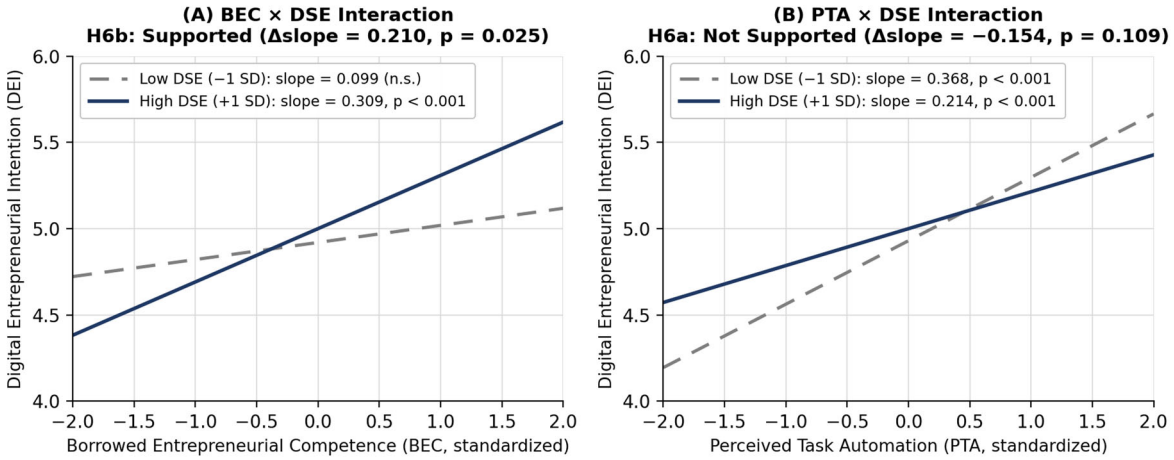


Figure A1. Asymmetric moderation by digital self-efficacy. Panel (**A**) shows the BEC × DSE interaction (H6b: supported); the BEC → DEI relationship is non-significant at low DSE but strong at high DSE, with the slope difference reaching statistical significance (Δslope = 0.210, $p = 0.025$). Panel (**B**) shows the PTA × DSE interaction (H6a: not supported); the PTA → DEI relationship is robust across both levels of DSE, with no significant slope difference (Δslope = −0.154, $p = 0.109$). The contrasting patterns illustrate that DSE selectively amplifies the agent-referenced (BEC) route, but not the tool-referenced (PTA) route. n.s. = not significant.

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